FORECASTING ISSUES IN PRESENT DAY POWER SYSTEMS

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ABSTRACT

In present day power systems, operational planning is a major concern. For successful operation of the power system a number of variables need to be forecasted with maximum accuracy over different forecasting horizons. However, different variables possess different characteristics and in literature different methodologies have been developed by the researchers for forecasting of these variables. Among many forecasting issues, three are of vital importance namely: (i) load forecasting, (ii) price forecasting, and (iii) wind speed and wind power forecasting. Load forecasting is essential for successful power system operation and control, while price forecasting is essential for risk management in deregulated electricity markets. As the level of penetration of renewable energy sources within the power system has increased, wind power forecasting has become important because of unique characteristics of wind energy and its effect on power system operation. Consequently a large number of researchers are working towards developing good and reliable forecasting models in the recent years and many different approaches have been developed. However, forecasting is a complex task and many exogenous variables interact in an intricate manner. Because of ever increasing complexity of the power system, forecasting these variables with maximum accuracy and minimum computational effort is still an open research issue. Considering these issues in mind, this thesis will focus on electricity load and price forecasting as well as wind power prediction. Different forecasting models will be developed based on time frame, specific application areas which are inadequately researched and forecasting technique. These models will also be compared with the results of the previous models available in the existing literature.

Keywords: Forecasting problem, load forecasting, price forecasting, wind power forecasting, time series, statistical methods, artificial intelligent techniques.

1. INTRODUCTION

1.1. Introduction: Almost all the countries are adopting deregulated industry structure for better utilization of the resources and for providing choice and quality service to the consumers at economical prices resulting in transparent price discovery [1]. In the current deregulated scenario, the forecasting of electricity load, price and wind power has emerged as one of the major research fields in electrical engineering. A lot of researchers and academicians are engaged in the activity of developing tools and algorithms for load, price and wind power forecasting. Whereas, electricity forecasting has reached in advanced stage of development [2], [3].

Global warming, widely regarded as one of the most critical problems facing mankind, has led to great emphasis on clean renewable energy resources such as solar, wind, and geothermal. Many nations have set ambitious goals for increasing the share of renewable energy in electric power generation - wind energy is expected to be a major contributor to the realization of these goals. However, at deep levels of penetration, the significant uncertainty and inherent variability in wind power pose major challenges to its integration into the electricity grid. In many regions around the world, wind power receives extra-market treatment in the form of feed-in tariffs which guarantee grid access and favorable fixed feed-in prices [5].

1.2. Forecasting Issues: The above Fig. 1.1 shows the different forecasting issues in power systems and these are described as given below:

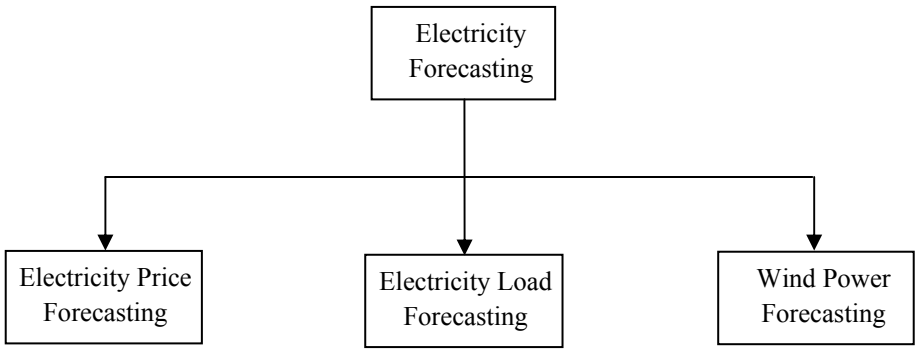

Fig. 1.1 Different forecasting issues in power systems

1.2.1 Electricity Load Forecasting: Load forecasting is a process to predict load for a future period. Load forecasting encompasses forecasts on several time scales, ranging from hourly to yearly. The forecasting model considers a number of hours and includes load forecasting on an hourly time scale. This means that load forecasts in MWh/h are made each hour according to updated information for individual future hours [11].

1.2.2 Electricity Price Forecasting: Price forecasting is a process to predict price for a future period and it is also depend on the load. However, the main objective of electricity market is to maximize profits. Forecasting loads and prices in electricity markets are mutually intertwined activities, and error in load forecasting will propagate to price forecasting. Electricity price has its special characteristics. The main features that make it so specific are its non-storability of power, which implies that prices are strongly dependent on the power demand.

1.2.3 Wind Power Forecasting: The uncertainty associated with wind power originates from uncertainties in wind speed forecasts. This in combination with the rapid development of wind

farms generates a need for better wind power production forecasting methods. The higher forecast reliability lower the balancing costs become in the system, which in case of large-scale integration of wind power can imply substantial savings for the wind farm owners as well as better overall efficiency of the system [11]. One of the fundamental problems faced by power system operators is the variability and non-schedulable nature of wind farm power generation. These inherent characteristics of wind power have both technical and commercial implications for efficient planning and operation of power systems. Wind power prediction systems provide the information that how much wind power can be expected at which point of time in the next few days. Wind power forecasting is one of the most critical aspects in wind power integration and operation.

1.3 Need of Forecasting in Power Systems: The essential requirement of forecasting is for the operation and planning for the future. However the need of forecasting is given below:

- Decisions on operation planning, which is used for determining the economical location, type, and size of the future power plants.
- Generation and transmission maintenance and also for fuel scheduling.
- Generator Online/Offline Decisions (Arrangements for Maintenance) Unit Commitment Decisions and Economic Load Dispatch Planning Load Increment/Decrement Decisions.
- Decisions on transmission expansion and enhancement, generation augmentation, distribution planning and regional energy exchange.
- Necessary for successful negotiations of bilateral contracts between suppliers and consumer.
- Power Suppliers to build their bidding strategies and consumers can derive a plan to maximize their utilities using electricity purchased from pool.

1.4 Difficulties of Forecasting in Power Systems: One key aspect of price and load is their volatility. Price/Load volatility is not only important, but it is also crucial to calculate average annual prices and to derive them from bilateral contract prices. However, good price and load prediction and confidence interval estimation are difficult since bidding strategies used by participants are complicated, and various uncertainties interact in an intricate way. In most competitive electricity markets, the hourly price/load series presents the following characteristics [3], [10]:

- High frequency.
- Non constant mean and variance (non stationary series).
- Multiple seasonality (corresponding to a daily and weekly periodicity).
- Calendar effect (such as weekends and holidays).
- High volatility.
- High percentage of unusual prices (mainly in periods of high demand) due to unexpected or uncontrolled events in the electricity markets.
- The fundamental problems are the variability and non-schedulable nature of demand.
- Because of inherent characteristics of demand forecasting has both technical and commercial implications for efficient planning and operation of power systems.
- Electricity cannot be transported from one region to another one because of existing bottle-necks or limited transportation capacity.

2. LITERATURE REVIEW

In the technical literature, several techniques to forecast electricity prices, load and wind power forecasting have been reported, namely hard and soft computing techniques. The hard computing techniques include autoregressive integrated moving average (ARIMA), wavelet-ARIMA, and mixed model approaches. Usually, an exact model of the system is required and the solution is found using algorithms that consider the physical phenomena that govern the process. These approaches can be very accurate but they require lot of information & computation and the computational cost is very high [7], [16]. So in this section we discuss the various forecasting models of electricity price, load and wind power available in the existing literature.

Aggarwal et.al [2] discusses some of the electricity forecasting issues in electricity markets. The main methodologies used in electricity price forecasting have been reviewed in this paper. The following price-forecasting techniques have been covered: (i) stochastic time series, (ii) causal models, and (iii) artificial intelligence based models. The quantitative analysis of the work done by various authors has been presented based on (a) time horizon for prediction, (b) input variables, (c) output variables, (d) results, (e) data points used for analysis, (f) preprocessing technique employed, and (g) architecture of the model. The results have been presented in the form of tables for ease of comparison. Classification of various price-influencing factors used by different researchers has been done and put for reference. Application of various models as applied to different electricity markets is also presented for consideration.

Negnevitsky et.al [3] discussed about the main forecasting techniques used for power system applications. Available forecasting techniques have been discussed with focus on electricity load, price and wind power prediction. Forecasting problems have been classified based on time frame, application specific area and forecasting techniques. Appropriate examples based on data pertaining to the Victorian electricity market, Australia and the PJM electricity market, U.S.A. are used to demonstrate the functioning of the developed neural network (NN) method based on similar days approach to predict hourly electricity load and price, respectively. The other important problem faced by power system utilities are the variability and non-schedulable nature of wind farm power generation. These inherent characteristics of wind power have both technical and commercial implications for efficient planning and operation of power systems. To address the wind power issues, this paper presents the application of an Adaptive Neural Fuzzy Inference System (ANFIS) to very short-term wind forecasting utilizing a case study from Tasmania, Australia.

Aggarwal et.al [4] discussed a support vector machine for the price forecasting of Ontario electricity market. The wholesale price of the Ontario electricity market was forecasted by splitting the time series into 24 series, one for each hour of the day. Then, a one-step ahead forecast for each hour of the next day for a test period of three years has been made using the respective hour–time series and by employing a support vector machine. A detailed sensitivity analysis was performed for the selection of model parameters. Furthermore, the performance of a support vector machine model was compared with a heuristic technique, simulation model, linear regression model, neural network model, neuro-fuzzy model; autoregressive integrated moving average model, dynamic regression model, and transfer function model. It was shown that the

proposed variable-segmented support vector machine model possessed better forecasting abilities than the other models and its performance was least affected by the volatility.

Bitar et.al [5] investigates how an independent wind power producer might optimally offer its variable power into a competitive electricity market for energy. They have started with a stochastic model for wind power production and a model for a perfectly competitive two-settlement market; they derive explicit formulae for optimal contract offerings and the corresponding optimal expected profit. As wind is an inherently variable source of energy, explore the sensitivity of optimal expected profit to uncertainty in the underlying wind process. They also examine the role of forecast information and recourse markets in this setting. They quantify the role of reserves in increasing reliability of offered contracts and obtain analytical expressions for marginal profits resulting from investments in improved forecasting and local auxiliary generation. The formulae make explicit the relationship between price signals and the value of such firming strategies.

Lobo et.al [6] proposed an aggregate prediction method based on the search for similarities between the current wind speed predictions in a set of locations and historical wind speed predictions. The aggregate power prediction is constructed from the measures of aggregate power generated during moments from a historical data set in which the wind speed predictions were similar to the current ones, using smoothing techniques. The methodology is applied to the hourly wind power forecast for the Spanish peninsular system, and compared with the predictions obtained with SIPREOLICO, the wind power prediction tool used by the Spanish system operator and also with the aggregate predictions provided by another forecasting agency. The proposed methodology shows considerably smaller prediction errors than the competitors.

Catalão et.al [7] proposes a novel hybrid approach for short-term wind power forecasting in Portugal. The proposed approach is based on the combination of wavelet transform (WT), particle swarm optimization (PSO), and adaptive-network- based fuzzy inference system (ANFIS). Their hybrid WPA approach is compared with persistence, NRM, ARIMA, NN, NNWT, NF, and wavelet-neuro-fuzzy (WNF) approaches, to demonstrate its effectiveness regarding forecasting accuracy and computation time.

Callaway et.al [8] developed sequential wind simulation models to forecast effective load-carrying capability (ELCC), but they produce data that follow a Gaussian distribution, which can be considerably different from real wind-speed distributions, and they do not explicitly model the influence of temperature on the evolution of wind speed. The latter issue is of significant importance considering the strength of correlation between electricity load and temperature and the influence electricity load shapes have on system reliability. This paper presents a new approach to reliability estimation of wind facilities that models wind-speed distributions none parametrically and includes the effect of temperature on the evolution of wind speed. A relatively long tall tower anemometer dataset is then used to test whether or not the model output produces ELCC distributions that are statistically similar to observed distributions. Results indicate that, relative to temperature independent models, temperature-dependent time series models are better at both short-term wind-speed forecasting and long-term reliability forecasting. Results also show that reliability forecasts are relatively unaffected by the shape of the wind speed distribution. Finally, it is apparent that model performance is robust to variation in the average wind power in the years used for model parameterization.

Aggarwal et.al [9] presents a wavelet transform (WT) based neural network (NN) model to forecast price profile in a deregulated electricity market. The historical price data has been decomposed into wavelet domain constitutive sub series using WT and then combined with the other time domain variables to form the set of input variables for the proposed forecasting model. The behavior of the wavelet domain constitutive series has been studied based on statistical analysis. It has been observed that forecasting accuracy can be improved by the use of WT in a forecasting model. Multi-scale analysis from one to seven levels of decomposition has been performed and the empirical evidence suggests that accuracy improvement is highest at third level of decomposition. Forecasting performance of the proposed model has been compared with (i) a heuristic technique, (ii) a simulation model used by Ontario's Independent Electricity System Operator (IESO), (iii) a Multiple Linear Regression (MLR) model, (iv) NN model, (v) Auto Regressive Integrated Moving Average (ARIMA) model, (vi) Dynamic Regression (DR) model, and (vii) Transfer Function (TF) model. Forecasting results show that the performance of the proposed WT based NN model is satisfactory and it can be used by the participants to respond properly as it predicts price before closing of window for submission of initial bids.

Amjady et.al [10] discusses the need, difficulties and methodologies used in energy price forecasting. Magnus Olsson et.al [11] discusses the impact of wind power into power systems demand for real-time balancing due to the stochastic nature of wind power production. The overall aim of this paper is to present probabilistic models of the impact of large-scale integration of wind power on the continuous demand in MW for real-time balancing power. This is important not only for system operators, but also for producers and consumers since they in most systems through various market solutions provide balancing power. Since there can occur situations where the wind power variations cancel out other types of deviations in the system, models on an hourly basis are not sufficient. Therefore the developed model is in continuous time and is based on stochastic differential equations (SDE). The model can be used within an analytical framework or in Monte Carlo simulations.

Yun et.al [12] makes a model to forecast short term load is established by combining the radial basis function (RBF) neural network with the adaptive neural fuzzy inference system (ANFIS). The model first makes use of the nonlinear approaching capacity of the RBF network to forecast the load on the prediction day with no account of the factor of electricity price, and then, based on the recent changes of the real-time price; it uses the ANFIS system to adjust the results of load forecasting obtained by RBF network. This system integration will improve forecasting accuracy and overcome the defects of the RBF network.

Almeshaiei et.al [13] presents a pragmatic methodology that can be used as a guide to construct Electric Power Load Forecasting models. This methodology is mainly based on decomposition and segmentation of the load time series. Several statistical analyses are involved to study the load features and forecasting precision such as moving average and probability plots of load noise. Real daily load data from Kuwaiti electric network are used as a case study.

Zhao et.al [14] gives a survey on the main methods of wind power forecasting (WPF). Wang et.al [15] provides a review on comparative analysis on the foremost forecasting models, associated with wind speed and power, based on physical methods, statistical methods, hybrid

methods over different time-scales. Furthermore, this paper gives emphasis on the accuracy of these models and the source of major errors, thus problems and challenges associated with wind power prediction are presented.

Catalão et.al [16] proposes novel hybrid approach, combining wavelet transform, particle swarm optimization, and adaptive-network-based fuzzy inference system, is proposed in this paper for short-term electricity prices forecasting in a competitive market. Results from a case study based on the electricity market of mainland Spain are presented. A thorough comparison is carried out, taking into account the results of previous publications.

Motamedi et.al [17] proposes a hybrid forecasting framework in smart grid enviournment that takes such dynamics into account when forecasting electricity price and demand. The proposed framework combines a multi-input multi output (MIMO) forecasting engine for joint price and demand prediction with data association mining (DAM) algorithms. In this framework, a DAM-based rule extraction mechanism is used to determine and extract the patterns in consumers' reaction to price forecasts. The extracted rules are then employed to fine-tune the initially generated demand and price forecasts of a MIMO engine. Simulation results are presented using Australia's and New England's electricity market data.

Bhaskar et.al [18] proposed a statistical-based wind power forecasting without using numerical weather prediction (NWP) inputs is carried out in this work. The proposed approach consists of two stages. In stage-I, wavelet decomposition of wind series is carried out and adaptive wavelet neural network (AWNN) is used to regress upon each decomposed signal, to predict wind speed up to 30 h ahead. In stage-II, a feed-forward neural network (FFNN) is used for nonlinear mapping between wind speed and wind power output, which transforms the forecasted wind speed into wind power prediction. The effectiveness of the proposed method is compared with persistence (PER) and new-reference (NR) benchmark models and the results show that the proposed model outperforms the benchmark models.

Barbounis et.al [19] deals with the problem of long-term wind speed and power forecasting based on meteorological information. Hourly forecasts up to 72-h ahead is produced for a wind park on the Greek island of Crete. As inputs models use the numerical forecasts of wind speed and direction provided by atmospheric modeling system SKIRON for four nearby positions up to 30 km away from the wind turbine cluster. Three types of local recurrent neural networks are employed as forecasting models, namely, the infinite impulse response multilayer perceptron (IIR-MLP), the local activation feedback multilayer network (LAF-MLN), and the diagonal recurrent neural network (RNN). These networks contain internal feedback paths, with the neuron connections implemented by means of IIR synaptic filters. Two novel and optimal on-line learning schemes are suggested for the update of the recurrent network's weights based on the recursive prediction error algorithm. The methods assure continuous stability of the network during the learning phase and exhibit improved performance compared to the conventional dynamic back propagation. Extensive experimentation is carried out where the three recurrent networks are additionally compared to two static models, a finite-impulse response NN (FIR-NN) and a conventional static-MLP network. Simulation results demonstrate that the recurrent models, trained by the suggested methods, outperform the static ones while they exhibit significant improvement over the persistent method.

Zhou et.al [20] proposes a new short-term forecasting algorithm for congestion, LMPs, and other power system variables based on the concept of system patterns combinations of status flags for generating units and transmission lines. The advantage of this algorithm relative to standard statistical forecasting methods is that structural aspects underlying power market operations are exploited to reduce forecast error. The advantage relative to previously proposed structural forecasting methods is that data requirements are substantially reduced. Forecasting results based on a NYISO case study demonstrate the feasibility and accuracy of the proposed algorithm.

2.1. Objective: The objective of this thesis is given as:

1. To propose a novel approach for electricity prices, load and wind power forecasting.
2. To improve forecasting accuracy by considering the results of previous forecasting models.
3. To reduce modeling complexity and achieving results in an acceptable computation time.
4. The proposed models will be tested and predictions will be compared with historical models.

3. THRUST AREA OF RESEARCH

3.1 Introduction: Under the condition of electricity markets, the price of electricity is connected to the load. Price varies with demand, and consequently, demand influences the fluctuation of the price. Therefore fluctuation in electricity price certainly will lead to a change in load characteristics, and finally the price will also be influenced by the load [12]. In this section, we discuss about different forecasting problems and techniques in the area of electric load forecasting, energy price forecasting and wind power prediction [3].

3.2 Load forecasting: Load forecasting encompasses forecasts on several time scales, ranging from hourly to yearly. The forecasting model considers a number of hours and includes load forecasting on an hourly time scale. This means that load forecasts in MWh/h are made each hour according to updated information for individual future hours [11]. Load forecasting is a process to predict load for a future period. Application of load forecasting falls into different time horizons: long-term forecasting (from one year to ten years), medium-term forecasting (from several months to one year), short-term forecasting (from one-hour to one-week) and real-time or very short-term forecasting (in minutes). Long-term forecasts influence the decisions on generation and transmission planning, which is used for determining the economical location, type, and size of the future power plants. Medium-term load forecasts are necessary for generation and transmission maintenance, and also for fuel scheduling. Accurate short-term load forecasts are necessary for unit commitment and economic dispatch. Very short-term load forecasting is for minutes ahead and is used for automatic generation control (AGC).

Good confidence level has been achieved in load forecasting by researchers. Load forecasting has been challenge in the past due to following reasons. First, because the load series is complex and exhibits several levels of seasonality: the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Secondly, because there are many important exogenous variables and that must be considered, especially weather related variables. Table 3.1 shows Classification of load forecasting according to different time horizons.

Table. 3.1

S. No.	Type	Duration	Importance
1	Long Term	one year to ten years	Decisions on generation and transmission planning, which is used for determining the economical location, type, and size of the future power plants
2	Medium Term	several months to one year	Generation and transmission maintenance and also for fuel scheduling
3	Short Term	one-hour to one-week	Unit commitment and economic dispatch
4	Real Time or Very Short Term	Minutes	Minutes ahead and is used for automatic generation control

3.3 Price forecasting: The main objective of electricity market is to maximize profits. Forecasting loads and prices in electricity markets are mutually intertwined activities, and error in load forecasting will propagate to price forecasting. Electricity price has its special characteristics. The main features that make it so specific are at least three. One of them is its non-storability of power, which implies that prices are strongly dependent on the power demand. Another characteristic is the seasonal behavior of the electricity price at different level (daily, weekly and annual seasonality) and the third one is related to the question of its transportability. Furthermore, electricity price can rise by tens of or even hundreds of times of its normal value showing one of the greatest volatilities among all commodities. Electricity cannot be transported from one region to another one because of existing bottle-necks or limited transportation capacity. Application of forecasting methods common in other commodity markets can have a large error in forecasting the price of electricity. Table 3.2 shows Classification of price forecasting according to different time horizons

Table. 3.2

S. No.	Type	Duration	Importance
1	Long Term	one year to ten years	Decisions on transmission expansion and enhancement, generation augmentation, distribution planning and regional energy exchange
2	Medium Term	several months to one year	necessary for successful negotiations of bilateral contracts between suppliers and consumer
3	Short Term	one day-ahead	Power Suppliers to build their bidding strategies and consumers can derive a plan to maximise their utilities using electricity purchased from pool

In most competitive electricity markets, the hourly price series have the characteristics such as volatility, non-stationary properties, multiple seasonality, spikes and high frequency. These characteristics are due to events that may occur alternatively in a market. For instance, a price spike that is a randomized event can be caused by market power, and also by unexpected incidents such as transmission congestion, transmission contingency and generation contingencies. It can also be influenced by other factors such as fuel prices, generation unit operation costs, weather conditions, and probably the most theoretically significant factor, the balance between overall system supply and demand.

3.4 Wind power Forecasting: The uncertainty associated with wind power originates from uncertainties in wind speed forecasts. This in combination with the rapid development of wind farms generates a need for better wind power production forecasting methods. The higher forecast reliability, lower the balancing costs become in the system, which in case of large-scale integration of wind power can imply substantial savings for the wind farm owners as well as better overall efficiency of the system [11]. One of the fundamental problems faced by power system operators is the variability and non-schedulable nature of wind farm power generation. These inherent characteristics of wind power have both technical and commercial implications for efficient planning and operation of power systems. Wind power prediction systems provide the information how much wind power can be expected at which point of time in the next few days. Wind power forecasting is one of the most critical aspects in wind power integration and operation [3], [14], [15]. Table 3.3 shows classification of wind power forecasting according to different time horizons

Table. 3.3

S. No.	Type	Duration	Importance
1	Long Term	1 week to 1 year or more ahead	Maintenance Scheduling to Obtain Optimal Operating Cost, the Feasibility Study for Design of the Wind Farm
2	Medium Term	48(or 72) hours to 1 week ahead	Generator Online/Offline Decisions (Arrangements for Maintenance) Unit Commitment Decisions
3	Short Term	30 minutes to 48(or 72) hours ahead	Economic Load Dispatch Planning Load Increment/Decrement Decisions
4	Very Short Term	Few seconds to 30 minutes ahead	Electricity Market Clearing Wind Turbine Control

When considering the problem of wind power forecasting, a number of factors need to be considered. The first consideration is the prediction horizon or forecasting time frame of interest. The broad timescales can be considered as: (i) Turbulence (1 second−30 minutes); (ii) Synoptic Scale in the Spectral Gap (30 minutes−6 hours); (iii) Synoptic Scale (6 hours−7 days); and (iv) Climatic Scale (months to years). A wind forecasting time scale of less than 30 minutes is referred to as the turbulence time scale or more generally as the very short-term time scale.

Various studies have been conducted on power fluctuations from large wind farms and their effects on power system operations. Large ramp variations in the very short-term time scale can have significant impacts on both power system security and (depending on the bidding and dispatch intervals involved) on trading in deregulated electricity markets. The importance of achieving the best possible wind power forecasting accuracy in the very short-time scale is thus of paramount importance during significant large ramp events or periods of high volatility in wind farm power output In addition, wind power electric power generated from wind kinetic energy possesses unique characteristics and attributes that differentiate it from fossil-based electric power. Unlike fossil- based power, where the rate of energy throughput is completely controllable, wind power is intermittent, variable, and non-dispatchable. Indeed, wind generation could vary according to diurnal heating and cooling patterns or suddenly increase with a storm front. Without an energy storage system, wind energy being converted into electric power has to be consumed immediately. As a result, the economic value of wind generation is dependent on the relative synchronized timing of the wind and load patterns. During the on-peak period of the day, the production of wind generation commands a high value. While during off-peak periods, wind generation may provide very little value or could even be curtailed when there is no load to

serve. Furthermore, wind power generation does not lend itself readily to participate in the traditional generation scheduling process where controllable generators are scheduled to meet a variable load. Generation scheduling process with wind power must take into account the variability and intermittency characteristics. Therefore, certain power system resources must be allocated separately to hedge against non availability and variability of wind power during a low or no wind condition. These additional reserves increase the overall generation costs.

3.5 Process Flow Graph: Fig. 3.1 shows the process flow graph of forecasting methodology in power systems.

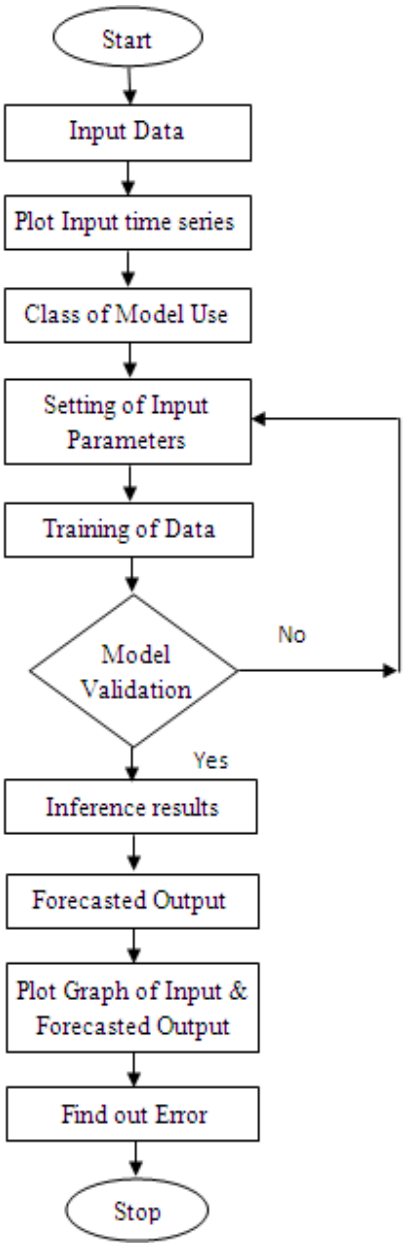

Fig. 3.1 Process flow graph of forecasting methodology

3.6 Forecasting Methodologies in Power Systems: Lots of methods have been developed for electricity price, load and wind power forecasting. However some of the methodologies are given below:

3.6.1 Load forecasting: Most forecasting models and methods have already been tried out on load forecasting, with varying degrees of success. Some of the models reported in literatures are multiplicative autoregressive models, dynamic linear or nonlinear models, autoregressive models, and methods based on Kalman filtering, Box and Jenkins transfer functions ARMAX models, optimization techniques, nonparametric regression. Several research works have been carried out on the application of artificial intelligence (AI) techniques, also termed as machine learning techniques, to the load forecasting problem. Various machine learning techniques reported in literatures are expert systems, fuzzy inference, fuzzy-neural models, artificial neural network (ANN), data mining, etc. Wu and Lu [21] proposed a machine learning technique by using data mining approach to forecast load. Fan et al. [22] discussed on integration of two machine learning techniques: Bayesian clustering by dynamics (BCD) and support vector regression (SVR) for day-ahead electricity load forecasting. Among the different techniques on load forecasting, application of NN technology for load forecasting in power system has received much attention in recent years. The main reason of NN becoming so popular lies in its ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques.

3.6.2 Price Forecasting: Electricity price forecasting models include statistical and non-statistical models. Time-series models, econometric models and intelligent system methods are the three main categories of statistical methods. The time-series techniques are successful in the areas where the frequency of the data is low, such as weekly patterns, but they can be problematic when there are rapid variations and high-frequency changes of the target signal. Non-statistical methods include equilibrium analysis and simulation methods. Methods based on machine learning techniques, especially the NNs are more common for electricity price forecasting due to their capability of learning complex and non-linear relationships that are difficult to model with conventional techniques. NN approach combined with similar day's method to forecast day-ahead prices in the PJM market. A machine learning technique by using mutual information technique and cascaded neuro-evolutionary algorithm for day-ahead price forecasting. Aggarwal et.al [4] has proposed Variable-segmented Support Vector Machine and Wavelet Transform in Artificial Neural Network based model for day-ahead price forecasting in Ontario Electricity Market.

3.6.3 Wind Power Forecasting: Several techniques have been identified for wind forecasting. These techniques can be categorized into numeric weather prediction (NWP) methods, statistical methods, methods based upon NNs, and hybrid approaches. Some researchers discussed NWPs estimator models based on machine learning technique using fuzzy logic and wind power forecasting models using NNs combination. NWP based techniques are well established for wind parameter forecasting with a prediction horizon of several hours or more. NWP methods could be the most accurate technique for short-term forecasting. However, in general, statistical, NN methods, or several advanced hybrid methods based on observations perform more accurately over the very short-term forecast range.

In general, forecasting techniques for very short-term wind power prediction use recent historical data as inputs to suitably structured models. These techniques include the simple persistence approach, classical linear statistical models such as Moving Average (MA), Auto-Regressive Moving Average (ARMA) and the Box-Jenkins approach based on Auto- Regressive Integrated Moving Average (ARIMA) or seasonally adjusted ARIMA models, also known as SARIMA models.

The statistical time series and NN methods are mostly aimed at short-term predictions. Typical time series models are developed based on historical values. They are easy to model and capable to provide timely prediction. In several predictions, they use the difference between the predicted and actual wind speeds in the immediate past to tune the model parameters. The advantage of the NN is to learn the relationship between inputs and outputs by a non-statistical approach Fig.3.2 shows the different types of forecasting models in power systems:

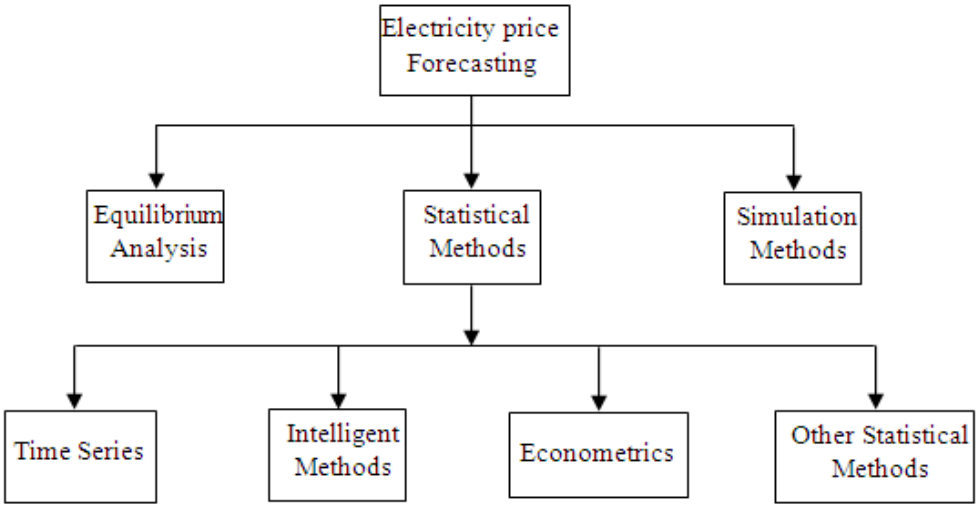

Fig. 3.2 Different types of forecasting models

3.7 Evaluation and Accuracy and the Source of Error: Now we turn to another fundamental concern how to measure the suitability of any particular forecasting methodology. In most of the forecasting methods accuracy is the criterion for selecting a particular method for the forecasting. For a consumer accuracy of forecasting is most important. The various methods for accuracy calculation given below:

- **The Error**

$$E = (Y_t - F_t)$$

Y_t, is actual observation for time period t
F_t, is forecast for same period t

- **The Mean Error (ME)**

$$ME = \frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)$$

- **The Mean Absolute Error (MAE)**

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t|$$

- **The Mean Square Error (MSE)**

$$MSE = \frac{1}{n}\sum_{t=0}^{n}(Y_t - F_t)^2$$

- **The Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=0}^{n}(Y_t - F_t)^2}$$

- **Percentage Error**

$$PE = \left(\frac{Y_t - F_t}{Y_t}\right) * 100$$

- **The Mean Percentage Error (MPE)**

$$MPE = \frac{1}{n}\sum_{n=1}^{t}\left(\frac{Y_t - F_t}{Y_t}\right) * 100$$

- **The Mean Absolute Percentage Error (MAPE)**

$$MAPE = \frac{1}{n}\sum_{n=0}^{n}|PE|$$

- **The Standard Deviation of Error (SDE)**

$$SDE = \sqrt{\frac{1}{n}\sum_{t=0}^{n}(ME - E)^2}$$

4. RESEARCH MOTIVATION

Almost all the countries are adopting deregulated industry structure for better utilization of the resources and for providing choice and quality service to the consumers at economical prices resulting in transparent price discovery [1]. In the present day power systems, a lot of researchers and academicians are engaged in the activity of developing tools, models and algorithms for load, price and wind power forecasting and is one of the major research fields in electrical engineering[2], [3].

Forecasting is a vital part of business planning in today's competitive environment. With increased penetration of renewable energy sources and introduction of deregulation in power

industry, many challenges have been encountered by the participants of the electricity market. Forecasting of wind power, electric loads and energy price have become a major issue in power systems. Following needs of the market, various techniques are used to forecast the wind power, energy price and power demand [3].

5. EXPECTED OUTCOMES

In the proposed thesis we will propose a novel approach for electricity prices, load and wind power forecasting to improve forecasting accuracy by comparing the results of previous forecasting models and we are also reduce modeling complexity and achieving results in an acceptable computation time. It is expected that with this research better models for forecasting promises from past may be produced.

6. TIME FRAMES

The timeframe schedule to be followed is given below:

Literature study time	4 months
Market Data collection time	2 months
Data Tabulation	2 months
Model Development	6 months
Model comparison & Validation	4 months
Publication of results in the form of research papers & conference papers	6 months

However depending upon the various conditions, this schedule may differ at the time of actual implementation.

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